ASSOCIATION BETWEEN INTRAOPERATIVE BLOOD PRESSURE VARIABILITY MEASURES AND IN-HOSPITAL MORTALITY IN CARDIAC SURGERY PATIENTS

by
Natasha Palamuttam

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ABSTRACT

Background and Objective: Observation and manipulation of intraoperative blood pressure have been a foundational anesthesia practice that have improved surgical outcomes but remain based on evidence from the 1970s and 1980s

The objective of this project is to explore the relationship between quantitative intraoperative blood pressure variability measures and postoperative outcomes. Additionally, we sought to evaluate which time frame of the surgery would best predict postoperative outcomes.

Methods: Several methods for summarizing blood pressure variability were calculated and compared. In particular, the derived parameters are Total Time Under (TTU) a MAP of 65 mmHg, Area Under the Threshold (AUT) and Area Above the Threshold (AOT) for thresholds ranging from 45-90mmHg and Generalized Average Real Variability of the mean arterial pressure (ARV-MAP). Analyses were then separately conducted on data subsets that contained measurements from the full surgery time, first hour of the surgery, and last hour of the surgery.

Results: ARV was slightly associated to in-hospital mortality (p=0.009) while TTU 65mmHg and AUT 65mmHg were both strongly associated to in-hospital mortality (p < 0.001). On average, measurements calculated using data from the full surgery were more highly associated to in-hospital mortality than their first hour or last hour counterparts. The best performing model utilized AUT 65mmHg and measurements calculated from the full surgery (AUC = 0.86).

Conclusions: In cardiac surgery, Measurement of intraoperative hypotension should the magnitude and time spent hypotension below the defined threshold of 65mmHg, to just the total time spent under 65 mmHg as previous studies suggest. While measures of hypotension are useful in predicting post-operative outcomes, their impact on the decision function is lower than that of preoperative features.

Thesis Advisors: Dr. Lee Goeddel, Dr. Paul Nagy, Dr. Harold Lehmann

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I. INTRODUCTION

1. Motivation

Observation and manipulation of intraoperative blood pressure have been a foundational anesthesia practice that have improved surgical outcomes but remain based in evidence from the 1970s and 1980s. Blood pressure is closely monitored because it is used as a proxy for estimating organ perfusion. Intraoperative hypotension is also related to various postoperative outcomes such as acute kidney injury and mortality [1, 2]. Mortality occurs in 2-3% of the 500,000 annual cardiac surgeries in the U.S. [3, 4]. Modern techniques provide higher resolution blood pressure measurements that can potentially be used to better predict postoperative morbidity and mortality. Current medical practice, however, operates on broad physiologic principles that are weakly based in evidence: blood pressure goals should be no less than a mean arterial pressure (MAP) of 65 mmHg or generally not less than 25% of baseline mean arterial pressure. This assertion develops into the central hypothesis of the project that intraoperative blood pressure data and derived variables from this data, can predict postoperative outcomes during cardiac surgery. In particular, the derived parameters are Total Time Under (TTU) a MAP of 65 mmHg, Area Under the Threshold (AUT) and Area Above the Threshold (AOT) for thresholds ranging from 45-90mmHg and generalized Average Real Variability of the mean arterial pressure (ARV-MAP) and our outcome of interest in this study is in-hospital mortality. These measures have been evaluated in patients that have undergone non-cardiac surgery and have been shown to have a correlation to 30-day mortality [5]. We aim to see if these measures of variability will have similar results when used in cohort of patients with cardiac surgery.

2. Objective

The objective of this project is to find a relationship between the derived features of intraoperative blood pressure and postoperative outcomes.

II. METHODS

1. Data Source

Our study utilizes data from the completely deidentified anesthesia aQI database. The intraoperative physiological dataset has been collected from 10,014 deidentified patients who had cardiac and noncardiac surgery. The data was collected over two years from July 1st, 2016, to October 6th, 2018.

2. Exclusion and Inclusion Criteria

We further filtered down the patients to include only the 1669 patients who received Cardiac Surgery. Patients with no discharge date, multiple surgeries, no intraoperative blood pressure data, insufficient (< 80% of the total surgery time) A-line measurements, and ASA Physical Status V or have been excluded from the dataset, leaving the final cohort count of 1,474 (Figure 1). When filtering for multiple surgeries, we kept their first chronological surgery.

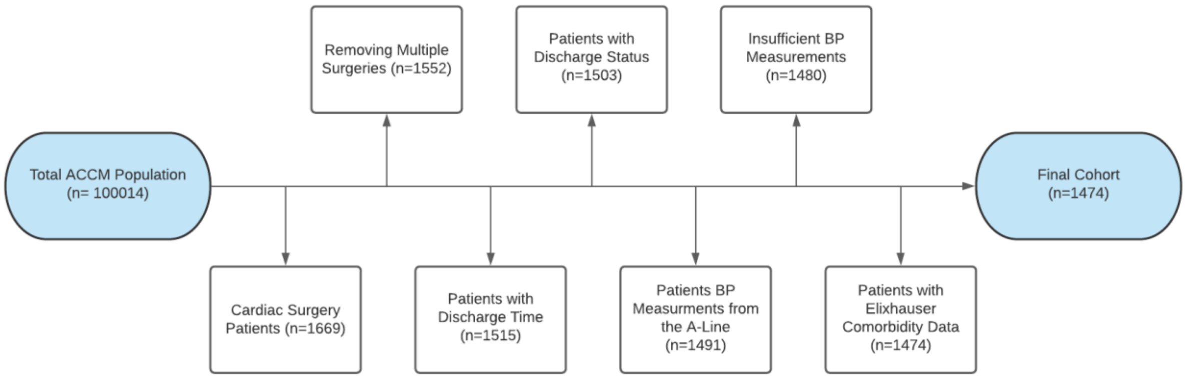


Figure 1. Exclusion Criteria

3. Derived Intraoperative Variables

3.1 Total Time Under a Threshold

Total Time Under is calculated as the time spent under certain thresholds. This value has historically been used qualitatively by physicians to assess blood pressure management during surgeries. The thresholds that were chosen to explore are under 65mmHg, 60mmHg, 55mmHg, 50mmHg, and 45mmHg. Additional we explore values above 70 mmHg, 75mmHg, 80mmHg, 85mmHg, and 90mmHg.

3.2 Area Under or Above a Threshold of Mean Arterial Blood Pressure

Mean Arterial Blood Pressure (MAP) is the average arterial pressure throughout one cardiac cycle of an individual and is considered as means to indirectly estimate the blood perfusion to organs in one's body. The equation for MAP is as shown below:

$$MAP = \frac{Systolic + 2(Diastolic)}{3}$$

MAP was analyzed over the course of surgery by examining the Area Under certain Thresholds (AUT)or Area Above certain Thresholds (AOT). This variable considers both the total time spent under or above the threshold as well as the magnitude of how far the patient fell below or above the threshold. The thresholds that were chosen to explore are under 65mmHg, 60mmHg, 55mmHg, 50mmHg, and 45mmHg. Additional we explore values above 70 mmHg, 75mmHg, 80mmHg, 85mmHg, and 90mmHg.

AUT and AOT were calculated using an implementation of Simpson's rule for integration provided by the integrate package in the SciPy Library.

Figure 2. Area Under 65mmHg Threshold for an Alive Patient

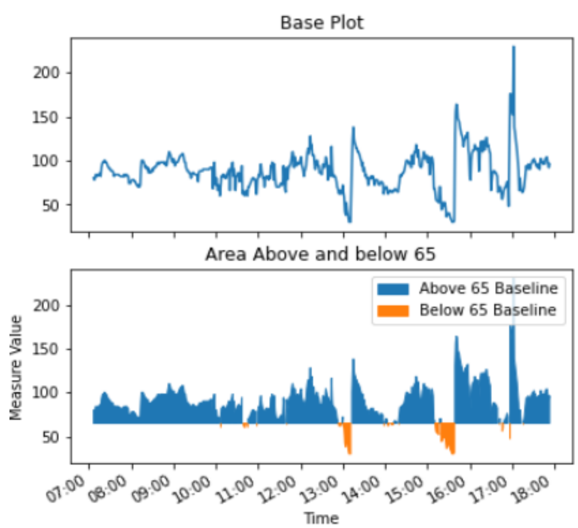
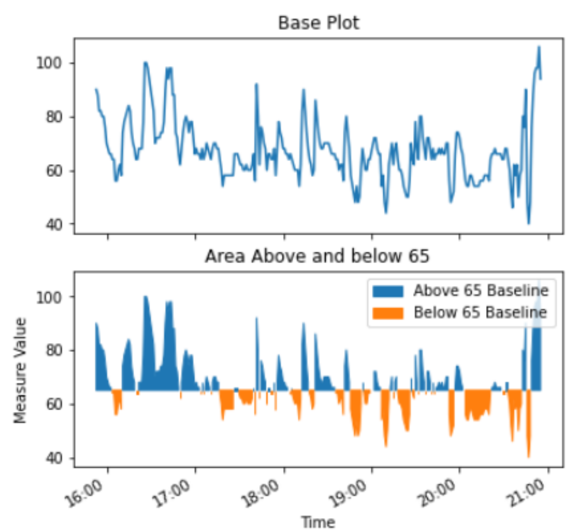


Figure 3. Area Under 65mmHg Threshold for a Deceased Patient



3.3 Average Real Variability

While there is no standardized measurement of blood pressure variability Hansen et al. [6] proposed an index for short-term reading blood pressure variability called average real variability (ARV). This equation calculates the sum of the product of time between measurements and absolute change divide by total time.

$$ARV = \frac{1}{\sum t} \sum_{k=1}^{n-1} w \times |BP_{k+1} - BP_k|$$

4. Preoperative Variables

4.1 Surgery Category

We further categorized all the Surgeries into one of 7 categories created by the Society of Thoracic Surgeons (STS): 1) Isolated Aortic Valve Replacement (AVR) 2) Isolated Mitral Valve Replacement (MVR) 3) Isolated Mitral Valve Repair (MV Repair) 4) Isolated Coronary Artery Bypass Grafting (CABG) 5) Combined AVR and CABG 6) Combined MVR and CABG 7) Combined MV Repair and CABG [7].

4.2 Comorbidity Score

We utilized the Healthcare Cost and Utilization Project's (HCUP) Elixhauser Comorbidity Index to identify comorbidities for our patient cohort [8]. We represent comorbidity burden as the total number of Elixhauser comorbidities a patient was identified with.

5. Univariate Analysis

All analyses were conducted using the TableOne package for Python.

5.1 Preoperative Variable Analysis

Categorical variables such as Gender, First Race, ASA Physical Status, and Surgery Category were evaluated using Chi-square and Continuous variables such as Age and Surgery Length were evaluated using two-sample test. We utilized Kruskal-Wallis for non-parametric variables for the Comorbidity Score.

5.2 Derived Intraoperative Variable Analysis

We calculated our derived features for three different time frames. The first-time frame utilized blood pressure measurements taken from the entire surgery. The second time frame only utilized blood pressure measurements taken from the first hour of the surgery. The last time frame only utilized blood pressure measurements taken from the last hour of the surgery. We evaluated each variable's association with our outcome of interest, in-hospital mortality, using the Kruskal-Wallis test for non-parametric variables. We used the p-values from the test to determine which derived intraoperative variables would be used in the final models.

6. Regression Models

6.1 Model Creation

Several Logistic Regression Models were created to assess the ability of our derived features and preoperative feature's ability to predict in-hospital mortality. Predictive Models were created using the Sklearn python package and the statsmodels python package. The cohort is extremely unbalanced with only 4% of the population experiencing our event of interest. To account for this, we utilized the class weights parameter in sklearn Logistic Regression model. The class weights penalize the model for the misclassification of the minority class.

6.2 Model Features

We narrowed our feature list down to 8 features. Utilizing variance inflation matrix shown in Table 1, we found that AUT under 65mmHg and TTU under 65mmHg were highly correlated. Knowing this we created one model without using either feature, one model utilizing only AUT under 65mmHg and one model utilizing only TTU under 65mmHg. This was then repeated for each surgery time frame. In total 18 models were created.

Table 1. Variance Inflation Factor for Model Features

Variable	**VIF**
Intercept	59.70
Age	1.03
Sex_M	1.15
SurgeryType_STSIsolated_CABG	1.07
Num_Elix_Comor	1.03
Surg_Length	2.21
ARV	1.78
TTU_65mmHg	5.20
AUT_65mmHg	4.95

6.3 Model Evaluation

To evaluate the model, we looked at the Accuracy, Area Under the Curve of the Receiver Operating Characteristic, the Sensitivity, and the Specificity. We also calculated the Coefficients of each feature as well as their confidence interval and p values for the models that did not utilize the class weights. This was due to the Sklearn package being unable to calculate these while the statsmodels package could. However, the statsmodels package was unable to set class weights.

III. RESULTS

1. Study Population Characteristics

Table 2 below illustrates our results from our univariate analysis of our preoperative features. Of our overall cohort of 1074 patients, 1030 had a hospital discharge status of Alive and only 44 had a discharge status of 44. Gender, Surgery Category, Surgery Length, and Number of comorbidities all had p-values below 0.05.

In this cohort males were more likely to have a discharge status of Alive. However, males made up a larger proportion of the study population. A significant portion of our population received an Isolated CABG surgery. On average, deceased patients had a surgery length 90 minutes longer than their alive counterparts. Deceased patients also often had one more comorbidity than their alive counterparts.

Table 2. Study Population Characteristics

		Grouped by Status					
		Missing	Overall	Alive	Deceased	P-Value	Test
	n		1074	1030	44		
Age, mean (SD)		0	64.1 (11.2)	64.0 (11.2)	66.5 (11.7)	0.162	Two Sample T-test
Gender, n (%)	**F**	0	286 (26.6)	264 (25.6)	22 (50.0)	0.001	Chi-squared
	M		788 (73.4)	766 (74.4)	22 (50.0)		
First Race, n (%)	**American Indian or Alaska Native**	0	1 (0.1)	1 (0.1)		0.906	Chi-squared
	Asian		67 (6.2)	63 (6.1)	4 (9.1)		
	Black or African American		163 (15.2)	156 (15.1)	7 (15.9)		
	Declined to Answer		1 (0.1)	1 (0.1)			
	Other		61 (5.7)	57 (5.5)	4 (9.1)		
	Unknown		6 (0.6)	6 (0.6)			
	White or Caucasian		775 (72.2)	746 (72.4)	29 (65.9)		
ASA Physical Status, n (%)	**II**	0	19 (1.8)	19 (1.8)		0.143	Chi-squared
	III		539 (50.2)	523 (50.8)	16 (36.4)		
	IV		506 (47.1)	479 (46.5)	27 (61.4)		
	Unknown		10 (0.9)	9 (0.9)	1 (2.3)		
Surgery Category, n (%)	**STS AVR + CABG**	0	85 (7.9)	76 (7.4)	9 (20.5)	<0.001	Chi-squared
	STS Isolated AVR		121 (11.3)	116 (11.3)	5 (11.4)		
	STS Isolated CABG		729 (67.9)	706 (68.5)	23 (52.3)		

	STS Isolated MVR		85 (7.9)	84 (8.2)	1 (2.3)		
	STS MV Repair		33 (3.1)	32 (3.1)	1 (2.3)		
	STS MV Repair + CABG		5 (0.5)	5 (0.5)			
	STS MVR + CABG		16 (1.5)	11 (1.1)	5 (11.4)		
Surgery Length, mean (SD)		0	354.3 (89.8)	349.3 (79.4)	470.3 (189.1)	<0.001	Two Sample T-test
Number of comorbidities, median [Q1,Q3]		0	3.0 [2.0,4.0]	3.0 [2.0,4.0]	4.0 [3.0,6.0]	<0.001	Kruskal-Wallis

2. Univariate Analysis of Derived Intraoperative Variables

Table 3 summarizes the results of the univariate analysis on derived intraoperative blood pressure variables when calculated using measurements from the entire surgery. When utilizing measurements from the full surgery the ARV was higher in patients that had a discharge status of deceased. The TTU 65mmHg not normalized to surgery length was also significantly larger in deceased patients. This trend continued when evaluating the AUT under thresholds 65mmHg, 60mHg, 55mmHg, 50mmHg, and 45mmHg. However, when evaluating the AOT for 70mmHg, 75mmHg, 80mmHg, 85mmHg, and 90mmHg there was less of a significant difference between the two populations.

Table 3: Derived Intraoperative Measurements for Full Surgery Time

	Grouped by Discharge Status					
	Missing	Overall	Alive	Deceased	P-Value	Test
n		1074	1030	44		
Avg_MAP, median [Q1,Q3]	0	73.7 [70.2,77.5]	73.7 [70.4,77.4]	73.3 [66.8,78.6]	0.315	Kruskal-Wallis
ARV, median [Q1,Q3]	0	1667.0 [1314.5,2073.0]	1663.0 [1312.5,2039.0]	1992.0 [1369.0,3212.5]	0.009	Kruskal-Wallis
TTU_under_65, median [Q1,Q3]	0	90.0 [60.0,128.0]	87.5 [59.2,125.0]	128.0 [75.5,223.8]	<0.001	Kruskal-Wallis
TTU_65_n, median [Q1,Q3]	0	0.3 [0.2,0.4]	0.3 [0.2,0.4]	0.3 [0.2,0.5]	0.037	Kruskal-Wallis
AUT_65, median [Q1,Q3]	0	576.6 [356.0,897.1]	567.7 [353.5,876.3]	885.7 [604.0,2153.3]	<0.001	Kruskal-Wallis
AUT_60, median [Q1,Q3]	0	232.1 [126.7,415.7]	229.0 [124.8,406.6]	427.8 [246.7,1141.5]	<0.001	Kruskal-Wallis
AUT_55, median [Q1,Q3]	0	88.0 [41.1,183.7]	85.7 [40.7,179.8]	198.3 [84.8,571.3]	<0.001	Kruskal-Wallis
AUT_50, median [Q1,Q3]	0	26.8 [6.9,72.7]	26.2 [7.0,69.2]	99.7 [5.8,272.2]	0.001	Kruskal-Wallis
AUT_45, median [Q1,Q3]	0	5.0 [-0.0,28.1]	5.0 [-0.0,26.0]	39.5 [-0.0,121.7]	<0.001	Kruskal-Wallis
AOT_70, median [Q1,Q3]	0	2348.7 [1549.5,3445.6]	2332.2 [1556.6,3385.3]	3029.7 [1329.2,5310.7]	0.050	Kruskal-Wallis
AOT_75, median [Q1,Q3]	0	1566.7 [924.2,2385.4]	1557.0 [924.2,2341.3]	1934.5 [933.7,3971.2]	0.051	Kruskal-Wallis
AOT_80, median [Q1,Q3]	0	970.3 [511.0,1625.5]	960.7 [510.7,1598.8]	1287.8 [558.3,2656.7]	0.057	Kruskal-Wallis
AOT_85, median [Q1,Q3]	0	599.0 [270.7,1108.1]	588.8 [270.7,1083.2]	920.0 [295.5,1858.5]	0.068	Kruskal-Wallis
AOT_90, median [Q1,Q3]	0	356.3 [135.5,739.7]	352.8 [135.8,711.3]	600.2 [114.0,1387.3]	0.093	Kruskal-Wallis

Table 4 summarizes the results of the univariate analysis on derived intraoperative blood pressure variables when calculated using only measurements from the first hour. When utilizing measurements only from the first hour of the surgery many of the derived variables were not significantly different in alive patients versus deceased patients. Most notably within the first hour most patients did not have blood pressure values fall below 60mmHg as seen by their interquartile ranges. Most of the blood pressure measurements were above 70mmHg.

Table 4.Derived Intraoperative Variables for First Hour of the Surgery

	Grouped by Discharge Status					
	Missing	Overall	Alive	Deceased	P-Value	Test
n		1074	1030	44		
Avg_MAP, median [Q1,Q3]	0	82.5 [75.5,90.1]	82.5 [75.5,89.9]	83.5 [71.4,93.9]	0.978	Kruskal-Wallis
ARV, median [Q1,Q3]	0	336.0 [242.5,448.0]	338.0 [244.5,449.5]	312.0 [167.5,424.5]	0.083	Kruskal-Wallis
TTU_65, median [Q1,Q3]	0	4.0 [0.0,11.0]	3.5 [0.0,11.0]	4.5 [0.0,11.8]	0.748	Kruskal-Wallis
TTU_65_n, median [Q1,Q3]	0	0.1 [0.0,0.2]	0.1 [0.0,0.2]	0.1 [0.0,0.2]	0.735	Kruskal-Wallis
AUT_65, median [Q1,Q3]	0	10.5 [-0.0,61.3]	10.3 [-0.0,61.2]	13.8 [-0.0,66.8]	0.775	Kruskal-Wallis
AUT_60, median [Q1,Q3]	0	0.0 [-0.0,17.2]	0.0 [-0.0,16.5]	0.0 [-0.0,19.8]	0.717	Kruskal-Wallis
AUT_55, median [Q1,Q3]	0	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.0 [-0.0,1.2]	0.742	Kruskal-Wallis
AUT_50, median [Q1,Q3]	0	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.429	Kruskal-Wallis
AUT_45, median [Q1,Q3]	0	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.468	Kruskal-Wallis
AOT_70, median [Q1,Q3]	0	775.5 [459.4,1198.5]	774.1 [462.5,1191.2]	828.3 [298.2,1394.7]	0.826	Kruskal-Wallis
AOT_75, median [Q1,Q3]	0	567.1 [294.8,947.1]	567.1 [298.1,939.7]	568.0 [186.8,1106.2]	0.811	Kruskal-Wallis
AOT_80, median [Q1,Q3]	0	387.0 [166.9,708.2]	387.4 [171.3,702.0]	381.7 [83.7,857.5]	0.703	Kruskal-Wallis
AOT_85, median [Q1,Q3]	0	252.9 [91.3,521.3]	254.1 [91.6,513.4]	220.6 [27.5,638.3]	0.560	Kruskal-Wallis
AOT_90, median [Q1,Q3]	0	156.3 [43.2,362.3]	157.3 [44.4,361.0]	117.8 [3.5,425.5]	0.438	Kruskal-Wallis

Table 5 summarizes the results of the univariate analysis on derived intraoperative blood pressure variables when calculated using only measurements from the last hour. When utilizing measurements only from the last hour of the surgery many of the derived variables were not significantly different in alive patients versus deceased patients. The groups only differed significantly when measuring the AUT 50mmHg or 45mmHg. However, most patients did not fall below the 50mmHg or 45mmHg threshold at all.

Table 5. Derived Intraoperative Variables for Last Hour of the Surgery

	Grouped by Status					
	Missing	**Overall**	**Alive**	**Deceased**	**P-Value**	**Test**
n		1074	1030	44		
Avg_MAP, median [Q1,Q3]	0	73.3 [68.4,79.1]	73.3 [68.4,79.1]	73.0 [66.8,78.9]	0.772	Kruskal-Wallis
ARV, median [Q1,Q3]	0	182.0 [140.0,252.0]	182.0 [140.0,250.0]	183.0 [142.5,268.0]	0.801	Kruskal-Wallis
TTU_65, median [Q1,Q3]	0	11.0 [3.0,23.0]	10.5 [3.0,23.0]	13.5 [3.8,27.5]	0.304	Kruskal-Wallis
TTU_65_n, median [Q1,Q3]	0	0.2 [0.1,0.4]	0.2 [0.1,0.4]	0.2 [0.1,0.5]	0.308	Kruskal-Wallis
AUT_65, median [Q1,Q3]	0	41.7 [5.0,117.2]	40.1 [5.0,115.1]	92.0 [7.8,179.0]	0.058	Kruskal-Wallis
AUT_60, median [Q1,Q3]	0	5.0 [-0.0,33.8]	5.0 [-0.0,32.8]	22.3 [-0.0,66.2]	0.016	Kruskal-Wallis
AUT_55, median [Q1,Q3]	0	0.0 [-0.0,5.2]	0.0 [-0.0,5.0]	1.0 [-0.0,17.0]	0.006	Kruskal-Wallis
AUT_50, median [Q1,Q3]	0	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.005	Kruskal-Wallis
AUT_45, median [Q1,Q3]	0	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	0.0 [-0.0,-0.0]	<0.001	Kruskal-Wallis
AOT_70, median [Q1,Q3]	0	311.3 [121.5,588.9]	309.7 [121.3,588.9]	331.6 [187.7,576.5]	0.609	Kruskal-Wallis
AOT_75, median [Q1,Q3]	0	161.3 [44.0,379.6]	159.5 [43.5,379.6]	184.3 [67.3,385.0]	0.461	Kruskal-Wallis
AOT_80, median [Q1,Q3]	0	387.0 [166.9,708.2]	387.4 [171.3,702.0]	381.7 [83.7,857.5]	0.703	Kruskal-Wallis
AOT_85, median [Q1,Q3]	0	252.9 [91.3,521.3]	254.1 [91.6,513.4]	220.6 [27.5,638.3]	0.560	Kruskal-Wallis
AOT_90, median [Q1,Q3]	0	156.3 [43.2,362.3]	157.3 [44.4,361.0]	117.8 [3.5,425.5]	0.438	Kruskal-Wallis

3. Logistic Regression Model Results

3.1 Sklearn Logistic Regression Model Metrics

Table 6 shows the results from each of the 18 models created. The models with ‘Base’ in their name indicate models that do not utilize either the AUT 65mmHg feature or the TTU 65mmHg feature. The models with ‘CW’ in their name indicate the models utilized class weights. The best performing model is the one created using measurements from the full surgery and that use the AUT 65mmHg feature. Most of the models of an ROC AUC around 0.75 while some dip below 0.65. While sensitivity is very high in most models, recall and specificity are very low with some nulls values.

Table 6. Model Evaluation Metrics

Model	ROC_AUC	FNR (Miss Rate)	Sensitivity	Specificity
Full Surgery Logistic Regression Base Model	0.746332	1	0	1
Full Surgery Logistic Regression AUT	0.747104	0.9	0.1	0.996138996
Full Surgery Logistic Regression TTU	0.800386	0.9	0.1	1
Full Surgery Logistic Regression CW Base	0.783398	0.4	0.6	0.806949807
Full Surgery Logistic Regression CW AUT	0.857143	0.1	0.9	0.737451737
Full Surgery Logistic Regression CW TTU	0.752896	0.3	0.7	0.733590734
First Hour Logistic Regression Base	0.721236	1	0	1
First Hour Logistic Regression AUT	0.595367	1	0	1
First Hour Logistic Regression TTU	0.723552	1	0	1
First Hour Logistic Regression CW Base	0.65251	0.6	0.4	0.683397683

First Hour Logistic Regression CW AUT	0.588031	0.7	0.3	0.691119691
First Hour Logistic Regression CW TTU	0.666409	0.5	0.5	0.67953668
Last Hour Logistic Regression Base	0.683012	1	0	1
Last Hour Logistic Regression AUT	0.737838	1	0	1
Last Hour Logistic Regression TTU	0.683784	1	0	1
Last Hour Logistic Regression CW Base	0.660618	0.6	0.4	0.691119691
Last Hour Logistic Regression CW AUT	0.715444	0.4	0.6	0.698841699
Last Hour Logistic Regression CW TTU	0.662548	0.6	0.4	0.691119691

3.2 Statsmodels Logistic Regression Model Metrics

Table 7 shows the coefficient values from each of the 9 models created using the Statsmodels python package. Each cell contains the coefficient value, the confidence interval in brackets and the p-value. Based on the coefficient for Sex_M, this feature played a large role in the decision of the function. This aligns with our earlier results from the univariate analysis. All three derived intraoperative blood pressure variables, ARV, AUT 65mmHg, TTU 65mmHg, had relatively small coefficient values indicating they weren’t as important in swaying the decision function.

Table 7. Coefficients of Variables in Models

	Age	Number of Comorbidities	Surgery Length	Sex_M	Surgery Type Isolated CABG	ARV	AUT 65mmHg	TTU 65mmHg
Full Surgery no AUT or TTU	-0.05 [-0.07 -0.04] p=0.0	0.01 [-0.17 0.2] p=0.89	0.0 [-0.0 0.01] p=0.1	-1.22 [-1.9 -0.54] p=0.0	-0.88 [-1.57 -0.19] p=0.01	0.0 [-0.0 0.0] p=0.3	NA	NA
Full Surgery no TTU	-0.05 [-0.07 -0.03] p=0.0	0.0 [-0.18 0.19] p=0.98	0.0 [-0.0 0.01] p=0.33	-1.37 [-2.07 -0.68] p=0.0	-0.72 [-1.43 -0.0] p=0.05	0.0 [-0.0 0.0] p=0.49	0.0 [0.0 0.0] p=0.03	NA
Full Surgery no AUT	-0.05 [-0.07 -0.03] p=0.0	0.01 [-0.17 0.2] p=0.91	0.0 [-0.0 0.01] p=0.32	-1.28 [-1.97 -0.58] p=0.0	-0.82 [-1.52 -0.11] p=0.02	0.0 [-0.0 0.0] p=0.3	NA	0.0 [-0.0 0.01] p=0.41
First Hour Surgery no AUT or TTU	0.02 [-0.01 0.05] p=0.14	0.26 [0.08 0.43] p=0.0	-0.07 [-0.11 -0.03] p=0.0	-0.71 [-1.44 0.03] p=0.06	-0.64 [-1.36 0.07] p=0.08	-0.0 [-0.0 0.0] p=0.22	NA	NA
First Hour Surgery no TTU	0.03 [-0.01 0.06] p=0.1	0.27 [0.09 0.44] p=0.0	-0.07 [-0.11 -0.04] p=0.0	-0.71 [-1.44 0.03] p=0.06	-0.64 [-1.36 0.08] p=0.08	-0.0 [-0.0 0.0] p=0.27	-0.0 [-0.01 0.0] p=0.19	NA
First Hour of Surgery no AUT	0.02 [-0.01 0.05] p=0.14	0.26 [0.08 0.43] p=0.0	-0.07 [-0.11 -0.03] p=0.0	-0.71 [-1.44 0.03] p=0.06	-0.64 [-1.36 0.07] p=0.08	-0.0 [-0.0 0.0] p=0.22	NA	0.0 [-0.03 0.04] p=0.9
Last Hour of Surgery no AUT or TTU	0.01 [-0.02 0.04] p=0.35	0.27 [0.09 0.45] p=0.0	-0.08 [-0.11 -0.04] p=0.0	-0.58 [-1.31 0.14] p=0.12	-0.72 [-1.44 -0.0] p=0.05	0.0 [-0.0 0.0] p=0.08	NA	NA

Last Hour of Surgery no TTU	0.01 [-0.02 0.04] p=0.4	0.27 [0.08 0.45] p=0.0	-0.08 [-0.11 -0.04] p=0.0	-0.6 [-1.33 0.13] p=0.11	-0.7 [-1.42 0.02] p=0.06	0.0 [-0.0 0.0] p=0.07	0.0 [-0.0 0.0] p=0.6	NA
Last Hour of Surgery no AUT	0.01 [-0.02 0.04] p=0.36	0.27 [0.09 0.45] p=0.0	-0.08 [-0.11 -0.04] p=0.0	-0.59 [-1.32 0.14] p=0.11	-0.72 [-1.44 0.0] p=0.05	0.0 [-0.0 0.0] p=0.08	NA	0.0 [-0.02 0.03] p=0.86

Figure 4. ROC Curve for Full Surgery Models

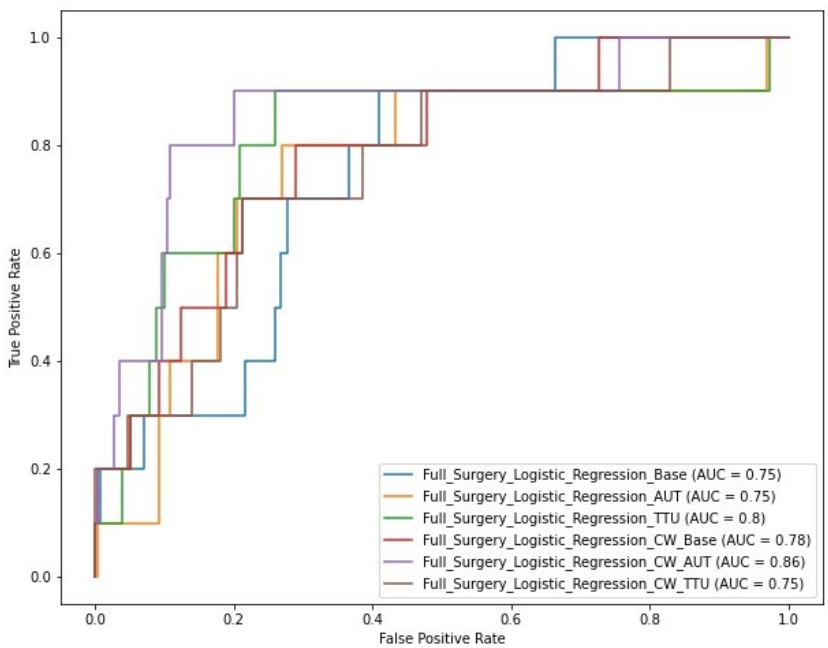


Figure 5. ROC Curve for First Hour Models

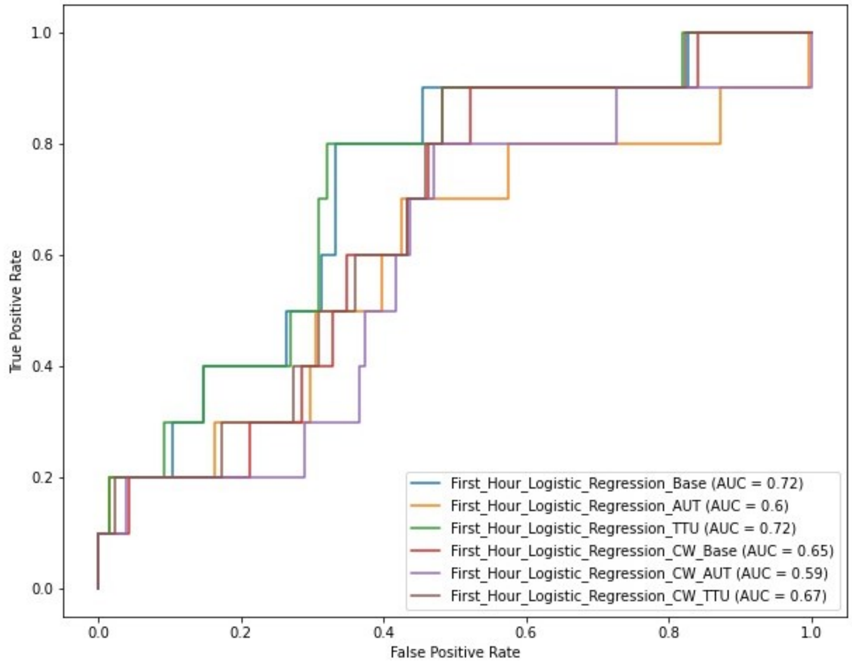
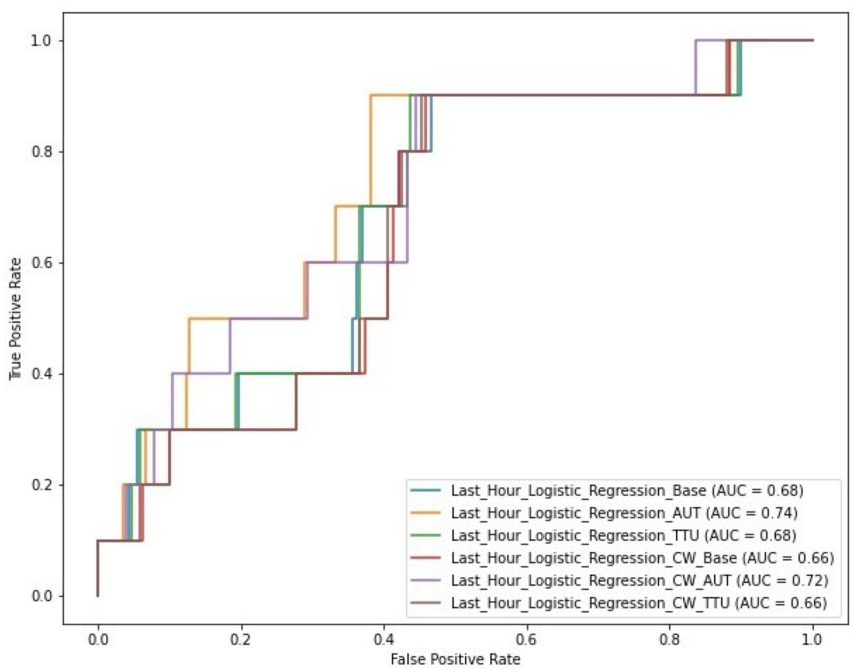


Figure 6. ROC Curve for Last Hour Models



IV. DISCUSSION

Our analysis included 1074 patients who underwent cardiac surgery between, of which 44 patients died in the hospital. We explored several intraoperative blood pressure variables calculated from the timeseries data of mean arterial blood pressure values. Our initial aim was to explore whether calculating these derived features at different blood pressure thresholds would show an association to in-hospital mortality. Our second aim was to see what portion of the surgery was most important to use for predicting in-hospital mortality.

From the results in Tables 3,4, and 5 we can conclude that the threshold to be used is 65mmHg which is consistent with multiple previous studies [1, 5]. In this data set blood pressure from the full surgery has a stronger association with in-hospital mortality than either the first or the last hour analyzed individually. This is partially due to the fact that blood pressure values do not deviate very far from the 65mmHg baseline in the first or last hour, therefore this data set may have been underpowered to adequately test this hypothesis that blood pressure evaluation from the first or last hour alone predicts post-operative outcome. This can also be a limitation caused by the limited number of datapoints used when constraining the collection to only a maximum of 60 datapoints (one data point per minute).

To address our primary hypothesis, we assessed whether total time spent under (TTU) a threshold would predict in-hospital mortality in combination with other preoperative features when compared to the area under a threshold (AUT). Models with AUT and class weights to account for the imbalanced classes performed better than models with TTU or models with no AUT or TTU.

Taking a closer look at all the full surgery models we see that the model with AUT and class weights, outperforms the model with TTU and class weights. Furthermore, this model has the highest sensitivity and the lowest False Negative Rate or miss rate, indicating that the model was able to capture many of the deceased patients unlike other models that were unable to capture any. However, the cost of capturing more deceased patients is misclassifying more alive patients as deceased, which lead to a lower specificity than other models.

V. CONCLUSION

Our overall aim was to compare different measures of intraoperative hypotension in patients that underwent cardiac surgery. We also aimed to compare these measures across different time frames of the patient's surgery. We have concluded that to obtain the most accurate and useful prediction we need to utilize data from the full surgery. models utilizing AUT consistently performed better if not the same as models that only relied on TTU.

Some limitations of this analysis can be attributed to our small sample size, which allowed us to only adjust for a few features. Logistic Regression is not a model that handles class imbalance and rare events data very well, but we believe these preliminary results will motivate future quantitative measurements intraoperative hypotension to predict a patient's trajectory post-surgery.

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